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Retrospective tillage differentiation using the Landsat-5 TM archive with discriminant analysis

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Abstract

Accurate and site-specific information on tillage practice is vital to understand the impacts of crop management on water quality, soil conservation, and soil carbon sequestration. Remote sensing is a cost-effective technique for surveillance and rapid assessment of tillage practice over large areas. A new empirical approach for accurately predicting tillage class using discriminant analysis (DA) on historical multi-temporal Landsat-TM 5 imagery has been developed. Ground truth data were obtained from the USDA-NRCS at 48 locations (20 conventional till [CT] and 28 conservation tillage or no-till [NT]). Classification accuracies were obtained for the DA models using reflectance values of Landsat-5 TM bands and Normalized Difference Tillage Index (NDTI) values. The performance of the DA models was compared with Logistic Regression (LR) models. On the basis of classification accuracy and kappa (κ) value, our results showed that the DA models performed better in tillage classification than the LR models. However, using NDTI values, both the DA and LR models performed similarly in tillage class discrimination. Model performance improved when a subset of locations rather than years was used. The results indicated broad-scale mapping of tillage practices is feasible using historical Landsat-5 TM imagery and DA-based classification.

1 | INTRODUCTION

Tillage is integral to crop production and has direct and indirect impacts on various biophysical processes of the environment. The Conservation Technology Information Center (CTIC) has defined tillage systems based on the amount of crop residue left on the soil surface after planting and resulting soil disturbance. Tillage practices that leave less than 15% crop residue cover after tillage and planting are defined as conventional tillage, whereas those retaining 30% or more crop residue and <20% of the soil surface as disturbed are labeled as no-till conservation tillage (CTIC, 2004). There are significant economic and environmental benefits from conservation tillage including, but not limited to, increased soil organic matter, improved soil tilth, reduced erosion, and increased soil productivity (CTIC, 2004). In the United States, governmental policies, such as the 1985 U.S. Farm Bill, the 2014 U.S. Farm Bill, and the Conservation Reserve

Abbreviations: CAI, cellulose absorption index; CRP, Conservation Reserve Program; CT, conventional tillage; CTIC, Conservation Technology Information Center; DA, discriminant analysis; DN, digital numbers; LCA, lignin–cellulose absorption index; LR, logistic regression; MD, Mahalanobis distance; NDTI, normalized difference tillage index; NT, conservation no-tillage; QDA, quadratic discriminant analysis; ROI, regions of interest; SINDRI, shortwave infrared normalized difference residue index; STI, simple tillage index; TM, Thematic Mapper.

Program (CRP), all have been implemented to encourage farmers to adopt no-till conservation tillage practices (Haché, Shibusawa, Sasao, Suhama, & Sah, 2007; Abraha, Gelfand, Hamilton, Chen, & Robertson, 2019; Lal & Kimble, 1997).

Information on tillage practices is critical in various process-based agroecosystem biogeochemical simulations and in the use of environmental indicators such as translocation of soil by erosion (Lobb, Huffman, & Reicosky, 2007). For guiding agri-environmental policies, it is important to monitor the adoption of conservation practices and persistence in conservation tillage decisions (Tran & Kurkalova, 2019). This requires acquiring historical and current tillage data over a period of years. Traditional in-situ and windshield observations for monitoring tillage practices, such as the Cropland Roadside Transect Survey (CTIC, 2004) provide county level assessments of tillage and crop residue through field surveys at .08- or 1.6-km (.5- or 1.0-mile) intervals. Such observation methods are expensive and time consuming and bear coarse spatial and temporal resolution, and may have some errors due to subjective quantitative estimation from one county to another (Daughtry, Doraiswamy, Hunt, Stern, & McMurtrey, 2006). Since the funding for the National Crop Residue Management Survey ended in 2004, there is a strong need to develop methods for accurate assessment of tillage practices over broad areas routinely as they are critical for modeling water and carbon dynamics within the soil–crop–atmosphere continuum.

Remote sensing techniques provide timely, accurate, and enhanced capacity to monitor tillage management based on difference between the values of spectral reflectance between soil and crop residue (Daughtry et al., 2006; Hively, Lamb, Daughtry, Shermeyer, & McCarty, 2018; Quemada, Hively, Daughtry, Lamb, & Shermeyer, 2018; Serbin, Hunt, Daughtry, McCarty, & Doraiswamy, 2009). Also, the use of historical time-series satellite imagery justifies as appropriate protocol for retrospective monitoring and assessment of tillage practices. Considering the advantages and limitations of spectral reflectance associated with different satellite images to assess tillage and crop residue cover, the Landsat-5 Thematic Mapper (TM) (Table 2) imagery has proven to be a good data source for tillage discrimination (Bricklemyer, Lawrence, Miller, & Battogtokh, 2006; Daughtry, 2001; Gowda, Howell, Evett, Chavez, & New, 2008; van Deventer, Ward, Gowda, & Lyon, 1997). The Landsat 5 satellite was launched on 1 Mar. 1984 and carried a Multispectral Scanner Subsystem and a Thematic Mapper onboard. According to the USGS, the Landsat 5 was decommissioned on 5 June 2013 due to failure of a redundant gyroscope. With more than 29 yr of processed and radiometrically calibrated data available at no cost, the Landsat-5 TM imagery archive offers the longest continuous synoptic view of the Earth at a 30-m spatial resolution and a unique opportunity to retrospectively study decadal land surface dynamics for, e.g., quantifying regional soil organic carbon sequestration, soil bulk density, soil moisture and productivity as evidenced in past studies (Baker, Ochsner, Ventera, & Griffis, 2007; Halvorson, Wienhold, & Black, 2002; Lal, Follett, & Kimble, 2003).

Core Ideas

- Discriminant analysis was found better than the logistic regression approach in classifying conventional and conservation no-till practices.
- Spatial scale was determined to be a better approach than temporal scale in classifying tillage practices.
- Discriminant analysis may prove useful to classify in other similar environments.

Various tillage indices such as simple tillage index (STI) (van Deventer et al., 1997), normalized difference tillage index (NDTI) (van Deventer et al., 1997), shortwave infrared normalized difference residue index (SINDRI) (Serbin et al., 2009), cellulose absorption index (CAI) (Nagler, Inoue, Glenn, Russ, & Daughtry, 2003), and lignin–cellulose absorption index (LCA) (Daughtry, Hunt, Doraiswamy, & McMurtrey, 2005) have been developed that maximize detection of crop residues and soil from their spectral signatures, thus enabling the discrimination of conventional and conservation tillage systems. In the literature various discriminative regression-based classifiers have been used to examine the relationship between tillage indices and crop residue. Often times, logistic regression (LR) models have often been used to classify tillage practices (DeGloria, Wall, Benson, & Whiting, 1986; Gowda et al., 2008; van Deventer et al., 1997). However, use of likelihood ratio classifiers, such as discriminant analysis, for tillage discrimination has seldom been reported (Wei, Ran, Du, & Yang, 2014). Recently, discriminant analysis for pattern recognition is gaining the attention of researchers in the field of spectrometry and spectroscopy (Balabin, Safieva, & Lomakina, 2010; Singh, Jayas, Paliwal, & White, 2009). There are many examples of the application of these multivariate statistical tools, e.g., classifying spoiled beef from unspoiled beef (Panigrahi, Balasubramanian, Gu, Logue, & Marchello, 2006), differentiating wheat (*Triticum aestivum* L.) classes (Mahesh, Manickavasagan, Jayas, Paliwal, & White, 2008), and detecting different fungal infection stages in canola (*Brassica napus* L.) (Senthilkumar, Jayas, & White, 2015). These results led us to hypothesize that discriminant analysis useful for tillage differentiation. Thus, the aims of the present study were: (i) to investigate the potential of discrimination analysis for tillage discrimination; and (ii) to compare the classification results with earlier tillage discrimination method using logistic regression.

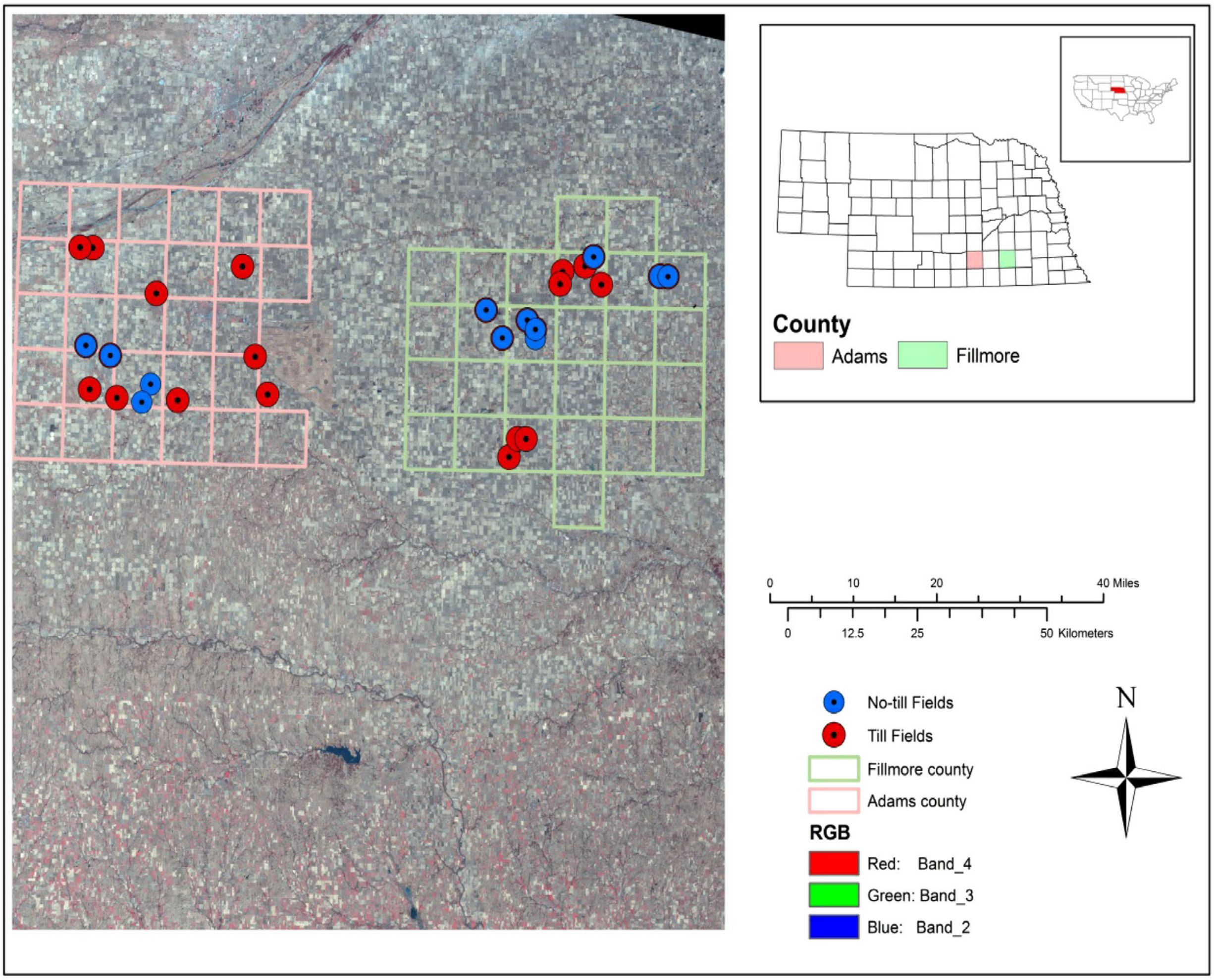

FIGURE 1 False color composite of the study area for June 2007. We include the Adam and Fillmore counties as they had the maximum number of fields with conventional till (CT) and conservation no-till (NT). The blue circles represent NT fields and the red circles indicate CT fields

2 | MATERIALS AND METHODS

2.1 | Study area and data

The study area is delimited by the Landsat-TM 5 Path 29/Row 32; covering Adams, Fillmore, Clay, Saline, and Webster counties of south-central Nebraska (Figure 1). This area is dominated by agricultural land use, with significant crops being corn (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.]. Planting dates for this region usually vary from early April for soybean and late April to early May for corn. Ground truth data for the tillage information was provided in the form of legal description by the USDA Natural Resources Conservation Service support staff (Sandra Weber, personal communication, 2012). Ground truth data on tillage practices were obtained from 48 randomly selected fields in these four counties. Out of 48 fields, 20 fields were reported as conventional till (CT) and 28 fields were reported as conservation no-till (NT). Most of the selected sites were located within Adams and Fillmore counties (centroids at 40.586°N, 98.388°W; 40.527°N, 97.596°W). Elevation of these two counties ranges from 457 to 520 m above sea level. Adams and Fillmore counties receive an average rainfall of 508 and 762 mm, with the addition of 381 and 558 mm of annual snowfall, respectively (http://www.climod.unl.edu). The dominant soil taxonomic classification for the study area is shown in Table 1.

2.2 | Image data acquisition

Post-emergence green vegetation has been found to confound crop residue signals and weaken our ability to observe tillage patterns from remotely sensed data products (Daughtry et al., 2005; Serbin et al., 2009; Zheng, Campbell, & de Beurs, 2012). Therefore, images acquired during June were selected because the seedling emergence of corn and soybean had already commenced, yet the crop canopy had not fully concealed evidence of the tillage practices during that period. The Landsat-5 TM images for June were acquired for our study area from 2006 to 2011 (7 June 2006, 10 June 2007, 12 June

TABLE 1 Characteristics of the soils evaluated in this study (USDA-NRCS, 2016)

Counties	Soil	Soil nomenclature
Adams	Holder	fine-silty, mixed, superactive, mesic Udic Argiustolls
	Coly	fine-silty, mixed, superactive, calcareous, mesic Typic Ustorthents
	Cozad	coarse-silty, mixed, superactive, mesic Typic Haplustolls
	Geary	fine-silty, mixed, superactive, mesic Udic Haplustafs
	Hasting	fine, smectitic, mesic Udic Argiustolls
	Hord	fine-silty, mixed, superactive, mesic Cumulic Haplustolls
Fillmore	Butler	fine, smectitic, mesic Vertic Argiaquolls
	Crete	fine, smectitic, mesic Udertic Argiustolls
	Hobbs	fine-silty, mixed, superactive, nonacid, mesic Mollic Ustifluvents
Clay	Crete	fine, smectitic, mesic Pachic Udertic Argiustolls
	Geary	fine-silty, mixed, superactive, mesic Udic Haplustalfs
	Hastings	fine, smectitic, mesic Udic Argiustolls
	Holder	fine-silty, mixed, superactive, mesic Udic Haplustalfs
Webster	Crete	fine, smectitic, mesic Pachic Udertic Argiustolls
	Hastings	fine, smectitic, mesic Udic Argiustolls
	Crete S	fine, smectitic, mesic Pachic Udertic Argiustolls
Saline	Hastings	fine, smectitic, mesic Udic Haplustalfs
	Muir	fine-silty, mixed, superactive, mesic Cumulic Haplustolls

2008, 2 June 2010, and 5 June 2011). Images with ≤15% cloud cover were included in the analysis. A cloud-free image was not available for 2009. Hence, 2009 was not included in this study.

2.3 | Image preprocessing

Processing of the Landsat-5 TM imagery was undertaken in the ERDAS Imagine version 9.3 (Leica Geosystems, Atlanta, GA). All bands from the Landsat-5 TM were analyzed for evaluating both discriminant analysis (DA) and LR models. For each of the 48 fields with ground truth data on tillage practices, a subset of pixels with a mean area of 1 km^2 was masked, creating regions of interest (ROI). Digital numbers (DN) within the ROI were converted to radiance, then to reflectance using the method and calibration coefficients as described in Chander and Markham (2003). Atmospheric correction was done using the values generated from the web-based tool developed by Barsi et al., 2003.

2.4 | Discriminant analysis

The statistical procedure PROC DISCRIM (Version 9.4, SAS Institute, Cary, NC) was used to perform DA to differentiate tillage classes using the indices and surface reflectance values from the Landsat bands. Tillage classes (NT and CT) were classified as 0 and 1, respectively. Ten classes were built from two tillage categories (CT and NT) for June 2006, 2007, 2008, 2010, and 2011. The decision to include bands or indices in the model was based on the corresponding coefficient of determination (R^2) and significant F-statistics ($p < .05$) using the stepwise method.

TABLE 2 Wavelength and resolution of Landsat-5 TM bands

TM band	Wavelength µm	Resolution m	Name
1	.45–.52	30	Blue
2	.52–.60	30	Green
3	.63–.69	30	Red
4	.76–.90	30	Near Infrared
5	1.55–1.75	30	Shortwave Infrared
6	10.40–12.50	120	Thermal Infrared
7	2.08–2.35	30	Shortwave Infrared

2.5 | Model calibration and validation

Models were developed using bands (Table 2) and indices (Table 3) from the methodology described in Zheng et al. (2012). In this methodology the log-ratio of posterior probabilities of the bands and the tillage indices, either belonging to CT and NT, are given by Eq. (1) and (2).

$$\xi = ln\frac{p}{q} = ln\frac{p_0}{q_0} - \frac{\delta_1 - \delta_2}{2} - \frac{1}{2}ln\frac{\left|\Sigma_1\right|}{\left|\Sigma_2\right|} \tag{1}$$

TABLE 3 List of Landsat-5 TM based indices used in our analysis

Tillage index	Band ratios	References
Simple Tillage Index (STI)	$\frac{\text{Band}_5}{\text{Band}_7}$	(Quemada & Daughtry, 2016)
Normalized Difference Tillage Index (NDTI)	$\left(\frac{\text{Band}_5 - \text{Band}_7}{\text{Band}_5 + \text{Band}_7}\right)$	(van Deventer et al., 1997)
M15	$\left(\frac{\text{Band}_1 - \text{Band}_5}{\text{Band}_1 + \text{Band}_5}\right)$	(van Deventer et al., 1997)
Soil Adjusted Vegetation Index (SAVI)	$\left[\frac{\text{Band}_4 - \text{Band}_3}{\text{Band}_4 - \text{Band}_3 + L}\right] \times (1 + L)$	(Huete, 1988)

$$\delta_i^2 = \left(\underline{x} - \underline{\mu_i}\right)' \sum_{\underline{i}}^{-1} \left(\underline{x} - \underline{\mu}_i\right) \tag{2}$$

where p_0 denotes the prior probability for the till class, (δ_i) is the squared Mahalanobis distance between $\underline{x}$ and $\underline{\mu_i}$ with respect to $\underline{\sum}_1$, $|\underline{\sum}|$ is the determinant of $\underline{\sum}$, and $\underline{\mu_i}$ and $\underline{\sum_i}$ are the group and covariance matrix, respectively (Yeager, Gregory, Key, & Todd, 2019). The significance of the means of the discriminant score for both tillage classes was checked using the Mahalanobis distance (Mahalanobis, 1936). This Eq. (2) assumes a common variance for the groups (CT and NT). A chi-square test was applied to determine whether the within covariance matrices in the discrimination function were significant or not (Morrison, 1990).

The DA procedure for each June scene for each year was implemented to generate a DA model for till and no-till tillage class. Performance of these models for each scene was evaluated using error matrices, producer's accuracy, user's accuracy, and kappa coefficient (κ). The κ statistic is a measure of agreement between instances classified by statistical method with the ground truth data. It can range from −1 to +1. Usually models with κ value ≤ .4 can be interpreted as fair agreement and κ value ≥ .4 can be interpreted as better agreement (McHugh, 2012). These indicators of model performance provide an effective way for accuracy assessment and have been explained in detail in several studies (Cohen, 1960; Congalton, Birch, Jones, & Schriever, 2002). Temporal validation comprised of identifying the model with the highest performance metrics for each till class and testing it in the scenes of the remaining years. Validation was also done on a pixel basis and on a field basis. For pixel-level validation, scene with highest classification accuracy was chosen. Seventy-five percent of the pixels from the scene was selected for training the DA model and the remaining 25% was used for testing the model. The subset of pixels as 10% of the total pixels from the scene with the highest classification were then divided into 75% and the performance of the selected model was also tested. For field-level validation, average reflectance value for each field was generated and the DA model was used to classify CT and NT on a temporal scale. In addition, performance of logistic regression models were compared with DA model.

TABLE 4 Stepwise summary for significant bands using region of interest (ROI) from Landsat-5 TM scenes

Step	Label[a]	Partial R^2	*F*-value
1	Band_6	.47***	23,736.4
2	Band_1	.3***	11,496
3	Band_7	.35***	14,158.2
4	Band_3	.16***	4,706.63
5	Band_2	.12***	3,256.2
6	Band_5	.11***	2,913.3
7	Band_4	.09***	2,439.4

[a]June scene for 2006–2008 and 2010–2011.
***Significance at P < .001.

3 | RESULTS

The significance test using Mahalanobis distance (MD) indicated that the distance was significant for the bands and tillage indices at the 5% level. Therefore, we concluded that there was a separation between tillage classes in all years. Moreover, results from the stepwise DA showed that all bands were significant ($p < .05$) (Table 4). These results corroborate prior studies (e.g., van Deventer et al., 1997; Viña, Peters, & Ji, 2003; Sullivan, Strickland, & Masters, 2008). For tillage indices, NDTI (partial $R^2 = .19, p < .05$) was identified as the best index for tillage class discrimination compared with STI and M15.

3.1 | Discriminant analysis

3.1.1 | Creating training and test datasets

Three approaches were implemented for training and testing the model: (i) train the model for each scene and test the best performing model across remaining years, (ii) train and test the model on a subset of pixels, and (iii) train and test the model using average reflectance value for each field. For the first approach, the DA model was used to classify tillage practices in all of the five images, and tillage class discrimination error matrix was calculated (Tables 5 and 6). Then

TABLE 5 Error matrices derived from Quadratic Discriminant Analysis (QDA) and Logistic Regression (LR) using select Landsat-5 TM scenes' (June) reflectance and Normalized Difference Tillage Index (NDTI) (van Deventer et al., 1997) values for discriminating conventional till (CT) and conservation till (NT)

			Conventional till		Conservation till			
Model	**Data**	**Scene**	**PA[a]**	**UA[b]**	**PA**	**UA**	**κ**	***Z***
QDA	Reflectance	6 June	67.3	63.3	63.3	85.0	.6	−19.08***
		7 June	91.4	77.3	77.3	89.0	.7	33.8***
		8 June	65.2	75.4	75.4	16.0	.5	61.6***
		10 June	67.3	66.8	66.8	79.8	.3	−24.3***
		11 June	65,3	62.8	62.8	83.0	.2	−16.9***
	NDTI	6 June	67.3	53.0	56.6	91.0	.0	−19.0***
		7 June	80.4	45.0	52.0	84.5	.3	33.8***
		8 June	62.0	99.2	42.2	.9	.0	61.6***
		10 June	65.4	32.3	61.0	86.1	.2	−24.3***
		11 June	65.3	14.9	62.8	90.6	.1	−16.9***
LR	Reflectance	6 June	62.4	80.9	62.1	39.1	.2	38.0***
		7 June	77.2	91.8	84.2	38.2	.6	113.9***
		8 June	66.0	93.3	66.3	21.8	.2	56.0***
		10 June	54.4	79.8	73.5	45.6	.2	62.7***
		11 June	53.8	80.4	73.3	43.9	.2	42.4***
	NDTI	6 June	55.4	11.5	56.6	92.6	.0	12.0***
		7 June	65.8	77.4	57.7	43.4	.2	44.1***
		8 June	62,0	99.9	.0	.0	.0	−1.3 NS[c]
		10 June	73.2	19.5	59.0	94.2	.1	49.4***
		11 June	55.5	11.7	56.2	92.3	.0	11.4***

[a]PA, producer's accuracy.
[b]UA, user's accuracy. [c] NS, not significant.
***Statistical significance at $P < .001$.

TABLE 6 Percent classification at pixel level in four June scenes (2006, 2008, 2010, and 2011) using June 2007 scene as the quadratic discriminant analysis (QDA) training model

Model	**Conventional till (CT) Classification accuracy**	**Conservation till (NT) Classification accuracy**
	%	
6 June	27	89
8 June	96	3
10 June	86	14
11 June	27	85

based on highest performance, 10 June 2007 image (user's accuracy [81% for CT and 89% for NT] and producer's accuracy [91.4% for CT and 77.3% for NT] with overall accuracy of 81% for CT and 89% for NT) with moderate agreement (κ = .7) (Table 5) was selected as the training model to validate/test on the remaining four scenes. The selected model when tested on the remaining 4 scenes resulted in 96 and 86% pixels correctly classified CT in June 2008 and 2010 scenes, respectively, whereas 89 and 85% of the total pixels were classified as NT in June 2006 and 2011 scenes, respectively (Table 6).

For the second approach, training and testing the DA model was carried out on a subset of pixels. Pixels were randomly selected to split into 75% training and 25% test data from June 2007 image. Discriminant analysis was performed on these pixels and the model performance was assessed. Results showed 61 and 80% producer's accuracy; and 74 and 68% for user's accuracy for CT and NT, respectively, with κ = .4. For testing the model, 10% of total pixels were subset from the image to perform DA. Seventy-five percent of the pixels were used for training and 25% for testing. Results showed no misclassification in the tillage classes. These results reinforce the fact that dividing the datasets as training and test in same image proved to be applicable in our study with respect to classification accuracy.

Various prior studies (Gowda, Dalzell, Mulla, & Kollman, 2001; South, Qi, & Lusch, 2004; Watts, Powell, Lawrence, & Hiker, 2011) have shown the importance of reflectance values at field scale for classifying the tillage practices. For evaluating the third approach, reflectance values for each band for the individual field (48 fields total, 20 fields CT, and 28 fields NT) were averaged. The DA model from the June 2007 scene was selected and applied to the averaged reflectance values for corresponding years and the number of fields that were

TABLE 7 Validation of the quadratic discriminant analysis (QDA) model at field scale using June 2007 scene as the training model. Numbers indicate total number of cases correctly identified for 20 conventional till (CT) and 28 conservation no-till (NT)

Date	Tillage	NT	CT	Total
6 June	NT	20	8	28
	CT	16	4	20
8 June	NT	6	22	28
	CT	4	16	20
10 June	NT	18	10	28
	CT	16	4	20
11 June	NT	23	5	28
	CT	7	13	20

correctly classified were reported (Table 7). Highest classification accuracy among the years was observed for 2011, with 23 fields correctly classified as NT and 13 fields correctly classified as CT (Table 7). Least classification on a field scale for NT was obtained for the 2008 scene (6 out of 28 correctly classified) and the 2010 scene for CT (4 out of 20 correctly classified).

Likewise, the DA model based on NDTI discriminated the tillage classes with varying degree of accuracy for the five scenes. Based on classification accuracy and κ-value, the DA model based on NDTI for the June 2007 scene was better compared with the rest of the four scences (Table 6). However, concerning a κ-value of .3 for the June 2007 scene, this model was not tested for other scenes across the years. Likewise, there was approximately 1% user's accuracy for NT with a κ-value of .0 for the year 2008. Moreover, with good performance for both producer's and user's accuracy for the year 2006, the κ-value was still .0, which implies a poor model (Table 5).

3.1.2 | Logistic regression

Accuracy indicators for discriminating the tillage classes with LR models were obtained using the June Landsat scenes' reflectance and NDTI. Results from model evaluation using reflectance values showed that the June 2007 scene had the highest classification accuracy (77.2% for CT and 84.2% for NT on producer's accuracy; 91.8% for CT and 38.2% for NT on user's accuracy) with a κ-value of .6 (Table 5) with overall accuracy of 61% for CT and 65% for NT. However, compared with the results from the DA model, the LR model had low performance in term of κ-value and user's accuracy for NT classification for most of the year (Table 5). However, in terms of producer's accuracy (based on reflectance value), the LR model performed as good as the DA-based model.

On the other hand, the NDTI-based LR model for 2007 had lower performance than the DA-based model in term of κ-value (Table 5). Moreover, the NDTI-based LR model for the June 2008 scene yielded 0% producer's and user's accuracy and a κ-value of .0 for NT. Hence, these results demonstrate that the DA model performed better for discriminating tillage classes than the LR models in our study.

4 | DISCUSSION

The contrasting result from both the DA and LR models based on reflectance and NDTI values highlights the importance of using the DA-based model for tillage classification at pixel scale, and also emphasized the important role of splitting the data set into training and test datasets. The striking difference in the result from using pixel and average field reflectance showed that picking a spatial unit is very important. The study was done on soybean fields in 10 states in the North Central region of the United States—Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Michigan (MI), Minnesota (MN), Ohio (OH), Nebraska (NE), North Dakota (ND), and Wisconsin (WI)—found that splitting data into train and test data at pixel scale may lead to an overestimation from the model. The reason was attributed to pixels being sampled within the same fields to be highly correlated (Azzari, Grassini, Edreira, Conley, & Mourtzinis, 2019). Cross-validation on the pixel scale was found better than the field scale in our study. However, extrapolation of the model developed from one year to other years and locations in a large area is not recommended. Although it is reasonable to get lower accuracy of tillage classification at field-level scale, as they are affected by the variability in mineralogy, brightness, color, texture, and organic matter (Bannari, Staenz, Champagne, & Khurshid, 2015). Moreover, the crop types in fields also played a pivotal role in tillage classification, as one study reported of an increased tillage class (CT vs. NT) separation in corn fields than soybean fields—presumably greater residual biomass in corn than soybean (Daughtry et al., 2005).

Several studies in the past also pointed out that spectral separability of tilled soils can be confounded by moisture/rainfall effects (Aggarwala, Colwell, & Reinhold, 1991; Seeley, Ruschy, & Linden, 1983; Weidong, Baret, Xingfa, Qingxi, & Lanfen, 2002). These result are comparable to our study where we had higher classification accuracy for NT in 2006 and 2011, and lower in 2008 and 2010. Contrarily, classification accuracy was lower for CT in 2006 and 2011, and higher in 2008 and 2010 using the reflectance value. We believe that the amount of rainfall on the scene acquisition day (±1 d) might have caused indifference in the classification accuracy (no rain observed during 2006, 2007, and 2011; 8.12 mm on 2008, and cumulative 7.84 mm on 1–3 June in 2010, respectively). The results were comparable to the performance of crop residue cover map based on the Landsat-7 and 8 with the changes in the moisture conditions (Hively, Shermeyer, Lamb, Daughtry, & Quemada, 2019). Even for the tillage indices NDTI that we used for both the DA and LR models in our study and Hively et al. (2019) studies, NDTI performed better to classify NT on no-rainfall events than on CT. For example, under high moisture conditions, there is easy separation of bare tilled soils with significant crop residue (Seeley et al., 1983). In high moisture conditions in CT, the bare soil decreases the reflectance in Bands 4, 5, and 7 (Table 2), whereas in NT conditions, there is an increase in the reflectance of all the three bands allowing for easy separation of soil and crop residue cover (Hively et al., 2019). These results were clearly evident in our study (Table 5), with the same result for CT with a no-rain event. These might be because our fields were scattered within five counties and combination of dry and moist fields at the same time. As for the visible bands as Bands 1, 2, and 3 (Table 2), the wet conditions make the soil and residue cover dark, making it hard to distinguish between them (Quemeda et al. 2016). Likewise, spectral reflectance was found to behave differently for different soil moisture levels, as low moisture level and high moisture level (Weidong et al., 2002) across 10 soil types in France. The high moisture levels in the abovementioned study are defined as soil moisture higher than the critical point of .17–.40 g cm^{-3}, whereas the low moisture levels are soil moisture below the critical point. In their study across 10 types of soil, they reported a non-linear relationship between soil moisture and spectral reflectance at low soil moisture levels, whereas linear relationships at high soil moisture levels (Weidong et al., 2002).

To our best understanding, the DA model has not been used before to assess tillage practices. Although, stepwise and linear discriminant analysis were used to differentiate corn varieties, crop/weed classification, and switch grass cultivars (Chen, Xun, Li, & Zhang, 2010; Foster, Kakani, Ge, & Mosali, 2012; Siddiqi, Lee, & Khan, 2014), the use of DA based model to classify and then validate at temporal and spatial scale for tillage classification is rare. This study provides a key step of understanding the dynamics of tillage classification at temporal and spatial scales. Although the use of the June 2007 calibration/training DA model was not effective in classifying tillage practices on temporal sampling (for different years), it was more effective in validating tillage practices on spatial sampling (subset of locations for the year 2007). Therefore, spatial scales can have a greater influence on discriminating tillage practices than the temporal sampling using the Landsat based TM DA model. This approach is expected to prove useful for future tillage classifications. In addition, the DA model proved more accurate classification of tillage practices than the LR model. The LR model was compared against DA models because they have been often used in the published literature for classifying tillage practices. The inability of LR models to classify tillage practices may be explained by the assumption of normally distributed and covariance matrices of two or more groups to be equal since the covariance matrices were not equal and data were not normally distributed in our study.

4.1 | Limitations

Some limitations of this study should be noted. First, when we apply the 2007 June scene as a calibration model to validate for the remaining four scenes on a temporal basis, misclassification in tillage practices occurred. The variability within a year likely inflated the uncertainty. Second, when we use 75% data and validated using 25% of the data on a spatial scale on the subset (10% of the image based on the best DA model), there was no misclassification of tillage practices. But when we used all the pixels based on the image from the best model, we observed misclassification in the result, so there lies uncertainty in the sample size on a pixel basis. Thirdly, data with explicit tillage location for fields is not readily available. Therefore, this DA model is not well suited to use if we want to use it for different years rather than a subset of locations.

5 | CONCLUSION

The DA used in our study discriminated tillage classes for June of 2006, 2007, 2008, 2010, and 2011. For the DA-based model, all bands were significant in predicting tillage practices, with Bands 6 and 1 explaining most ($R^2 > .77$) of the variations. Among the DA models, model based on the June 2007 image was determined the best and demonstrated the highest classification accuracy for both tillage classes. Moreover, the DA-based TM approach proved better than the LR model in classifying tillage practices, whereas the DA and LR models based on NDTI performed poorly. Despite the limitations, the developed DA models have been validated both on temporal and spatial scales. Based on our findings, we conclude that the DA provides a non-destructive, rapid means for identifying significant spectral bands for regional tillage class discrimination.

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DISCLOSURE

The authors have no relevant financial interests in the manuscript and no other potential conflicts of interest to disclose.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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